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Estimating rainfall and water balance over the Okavango River Basin for hydrological applications

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Abstract

A historical database for use in rainfall-runoff modeling of the Okavango River Basin in Southwest Africa is presented. The work has relevance for similar data-sparse regions. The parameters of main concern are rainfall and catchment water balance which are key variables for subsequent studies of the hydrological impacts of development and climate change. Rainfall estimates are based on a combination of in-situ gauges and satellite sources. Rain gauge measurements are most extensive from 1955 to 1972, after which they are drastically reduced due to the Angolan civil war. The sensitivity of the rainfall fields to spatial interpolation techniques and the density of gauges was evaluated. Satellite based rainfall estimates for the basin are developed for the period from 1991 onwards, based on the Tropical Rainfall Measuring Mission (TRMM) and Special Sensor Microwave Imager (SSM/I) data sets. The consistency between the gauges and satellite estimates was considered. A methodology was developed to allow calibration of the rainfall-runoff hydrological model against rain gauge data from 1960-1972, with the prerequisite that the model should be driven by satellite derived rainfall products for the 1990s onwards. With the rain gauge data, addition of a single rainfall station (Longa) in regions where stations earlier were lacking was more important than the chosen interpolation method. Comparison of satellite and gauge rainfall outside the basin indicated that the satellite overestimates rainfall by 20%. A non-linear correction was derived used by fitting the rainfall frequency characteristics to those of the historical rainfall data. This satellite rainfall dataset was found satisfactory when using the Pitman rainfall-runoff model (Hughes et al., this issue). Intensive monitoring in the region is recommended to increase accuracy of the comprehensive satellite rainfall estimate calibration procedure.

1. Introduction

The assessment of water resources of large river basins over southern Africa is often complicated due to limited data availability. Nevertheless, sustainable planning of water resources in the region requires information on the present spatial and temporal variability of rainfall, as well as the hydrological response to development policies and climate change (Hellmuth and Sanderson, 2001). In this context, it has been demonstrated that hydrological models can be a valuable tool, providing a common platform for experts, decision-makers and stakeholders. Consequently, the use of models for policy making has increased in the last decade (Alkan Olsson and Andersson, 2005). The availability of geographical and climatological data, with emphasis on rainfall information, is often more critical than the choice of complexity of the hydrological model used for the success of a model application (Gan et al., 1997).

The Okavango river basin spans three riparian states: Angola, Namibia and Botswana. Streamflow is mainly generated in Angola where the Cuito and Cubango rivers rise (see Kgathi et al., this issue for an overview). They then join and cross the Namibia/Angola border, before flowing into the wetlands of the Okavango alluvial fan in Botswana (Figure 1), known commonly as the Okavango Delta. The area of the basin that generates water to the delta is 165 000 km², of which 82% is situated in Angola. While much work has been undertaken on the ecology and hydrodynamics of the Okavango Delta (McCarthy and Ellery, 1998), little is known of the overall basin dynamics, especially the headwaters in Angola. This is partly due to the lack of rainfall and flow measurements during and after the Angolan civil war of 1975-2002. The Okavango River basin is situated far away from heavily populated areas and is thus relatively pristine. However, there are concerns that the resettlement of displaced communities in the Angolan part of the basin might change this (Green Cross

International, 2000). Moreover, it is likely that any future developments will occur against the background of climate change (Andersson et al., this issue). Integrated water resource management to assess present hydrological conditions and the impacts of potential developments and climate change on the river flow requires relevant hydro-climatological and geographical information, with sufficient resolution in time and space.

This paper describes the development and evaluation of such fundamental data for application in hydrological modeling of the Okavango River (Hughes et al., this issue) and delta (Wolski et al., this issue). Accurate estimation of rainfall is the primary requirement for hydrological modeling. This is particularly challenging for the Okavango basin since almost all the river flow is generated in the highlands of Angola, where data is most scarce. Here we describe the development of a gauge based rainfall dataset and satellite dataset for the period when gauge data is unavailable.

2. Data and methods

The hydrological model used in the Okavango study (Hughes et al., this issue) is a modified version of the Pitman model. The model is a semi-distributed model that requires monthly estimates of monthly rainfall at the sub-catchment scale over the 21 sub-catchments defined for the upper river basin (Figure 1). An initial study of rainfall gauge interpolation methods for the Okavango region by Ragnarsson (2002) showed that inverse distance weighting (IDW) provided lower errors than either spline or kriging for the period 1900-1974. After 1975 none of the methods were found satisfactory because of data scarcity. This paper presents an evaluation of the IDW and co-kriging methods for gauge interpolation, a

description of a new satellite based rainfall dataset and a technique to merge the gauge and satellite data into a unified dataset to drive the hydrological model.

2.1. Estimate of sub-basin rainfall time series from gauged data

Monthly observations of rainfall from rain gauges in a broad region which includes the Okavango river system were obtained from various sources including the Nicholson African monthly rainfall database (186 gauges, from the Miombo CD-Rom, 1997), the Servicio Meteorologico de Angola and the Meteorological Offices of Namibia and Botswana. The combined dataset included 242 gauges of which only 22 were situated within the Okavango basin, and nine of those in the Angolan headwaters, where most streamflow is generated (Figure 2). In the analysis the accuracy of both the Nicholson dataset and the full dataset (referred to as the extended dataset) are considered. The number of gauges in the wider region 16E-24E, 12S-22S fell from around 70 during the 1950s -early 70s to less than 5 in the 1990s. Many stations, especially in Angola suffer from long periods with missing data (Figure 2). Monthly rainfall data for the period 1960-1972 was used for calibration of the Pitman rainfall-runoff model (Hughes et al., this issue). Double mass plots on the stations' rainfall for this period, showed no notable deviations. Time series for each of the 21 sub-basins of monthly rainfall was constructed by interpolating the gauge station data (1960-72) to an 8 km equal area grid and then averaging this over each of the river sub-basins. The point rain gauge data were interpolated using two methods, inverse distance weighting (IDW) and co-kriging and the results evaluated.

The co-kriging interpolation method involves the use of physiographic features which correlate with rainfall to provide additional spatial information to assist the interpolation of gauge data. This can be especially useful in basins with a sparse rain gauge network (Wilk and Andersson, 2000). Correlations between average annual rainfall at the available stations

and a number of physiographic features including elevation, slope, aspect, distance to water divide and as well as vegetation were calculated with Pearson's and Kendall's tau-b nonparametric testing. Information about topography and land cover was obtained from the Miombo CD-Rom (1997). An additional vegetation map from the Global Vegetation Modeling Unit (www.gvm-jrd.it/glc2000) was also used. Vegetation from these maps was classified into 12 subjective groups where the densest vegetation was given the lowest class.

The accuracy of the IDW and co-kriging interpolated gauge data sets was evaluated using two complementary approaches. First, a cross-validation exercise was conducted which involved an iterative jack-knifing procedure in which individual stations were removed from the dataset and the interpolated values at that point compared to the observed value. The analyses were made for the wet season months (November-April) during the 1960-1972 period. The SE error of the regression coefficient between the observed and interpolated values was used to quantify accuracy

$$SE = SD \times (1-r^2)^{0.5} \quad (\text{Eq. 1})$$

where: SD = standard deviation of the monthly rainfall and , r^2 = coefficient of variation.

Three data sets were compared, IDW of the Nicholson rainfall records, IDW of the extended data set and co-kriging of the extended data set. The evaluation was conducted for two important headwater sub-basins with high rainfall, namely the Kubango in the western region draining into the Cubango River, and the Cuito in the east draining into the Cuito River (Figure 1).

Second, the hydrological rainfall-runoff river basin model (Hughes et al., this issue), calibrated using gauge data interpolated using data produced by the extended set by IDW was used in order to assess if and by how much the alternative sets of sub-basin interpolated time series of areal rainfall impacted on the hydrological simulations. No recalibration was performed, since a calibration procedure partially will compensate for errors in the data input

(Brath et al., 2004). Outputs from the hydrological model, driven by various rainfall databases were assessed for Kubango and Cuito (Figure 1). The accuracy of the hydrological simulation compared to the observed hydrograph was quantified using the coefficient of efficiency (Nash and Sutcliffe, 1970) in which a perfect fit has a coefficient of 1.

2.2. Remote sensing based rainfall estimates

For this study a new monthly rainfall dataset at 0.5° spatial resolution was developed for the period 1991-2002 from multiple satellite sources; namely the passive microwave (MW) Special Sensor Microwave Imager (SSM/I), Tropical Rainfall Monitoring Mission (TRMM) Microwave Imager (TMI) and the TRMM Precipitation Radar (PR). There are numerous existing satellite based gridded monthly rainfall datasets available (see New et al., 2001 for an overview). However, none satisfied the requirements of relatively high spatial resolution and a long historical period. The new dataset was based on integrating instantaneous estimates from a series of satellite MW sensors. These are known to provide more accurate estimates of rainfall than those from satellite infrared sensors such as Meteosat at the resolution required by the hydrological model (Adler et al., 2001). This is largely because clouds are relatively transparent at microwave wavelengths but hydrometeors are not, resulting in a relatively direct link between hydrometeors and attenuation of upwelling microwave radiation. In contrast at infrared wavelengths clouds are opaque so that rainfall must be inferred indirectly from cloud top characteristics. Despite the physically indirect nature of the infrared/rainfall, relationship Grimes et al. (2003) showed that within central/southern Africa a strong quantitative relationship exists between rainfall amount and appropriately calibrated cold cloud duration derived from Meteosat thermal infrared data. Unfortunately, over the Okavango catchment there are very limited rainguage data to calibrate the cold cloud duration data, although it was recognised that such an approach could provide a good alternative to the

approach taken here if accurate calibration data were available. Additionally it was recognised that no individual satellite sensor can provide truly unbiased estimates and so a range of corrections were developed to minimise bias, as described below.

Although the first SSM/I was launched in 1987 on board the Defence Meteorological Satellite Programs (DMSP) 5D-2 spacecraft, due to technical problems, continuous, reliable rainfall estimates are only available from 1991. Rainfall estimates from SSM/I data were retrieved using the Goddard Profiling Algorithm at 0.5° resolution on an orbit-by-orbit basis, and will subsequently be known as SGPROF (Kummerow and Giglio, 1994; Kummerow et al., 1996). The DMSP satellites are in a polar orbiting sun-synchronous orbit providing up to 2 overpasses each day in the tropics. Each of the SSM/I sensors launched since 1987 (on board the DMSP F8, F9, F10, F11, F13, F14 and F15 satellites) has a slightly different crossing time. When integrated over some time period (in this case 1 month) the rainfall estimates only sample a limited portion of the diurnal cycle and will have a resultant bias.

To overcome the diurnal bias in the SSM/I data information from the TRMM sensors was also utilised. The TRMM satellite, launched in 1997 in a low-earth non sun-synchronous orbit such that the diurnal cycle is sampled for each location on the Earth's tropical surface over the course of 23 days at the equator and 46 days at the highest latitudes (38°N and 38°S) (Negri et al., 2003). Rainfall estimates from TRMM are therefore less prone to systematic sampling errors associated with the diurnal cycle of rainfall if averaged over sufficient time. There are two rainfall sensors on board TRMM; a passive microwave radiometer (of the same type as the SSM/I) known as the TRMM Microwave Imager (TMI), and an active microwave sensor, the Precipitation Radar (PR). For each of these instruments there are operational algorithms, which provide estimates of rainfall. The TMI rainfall is estimated using the Goddard Profiling Algorithm, TGPROF (Kummerow et al., 2001). In addition, a rainfall product based on a combination (COMB) of PR and TMI is available, where the PR algorithm

is optimized for the distribution of rainfall particle sizes given by TMI (Haddad et al., 1997).

The rainfall data is provided orbit-by-orbit on a gridded 0.5° grid.

The removal of the diurnal bias is particularly important for the Okavango region where the diurnal cycle is pronounced. The diurnal cycle of rainfall derived from TRMM PR data over the Okavango catchment is dominated by the first harmonic with peak rainfall near 15.00GMT approximately 4 times higher than during the period of minimum rainfall around 09.00GMT. Rainfall occurs preferentially in the local afternoon (peaking at 15.00LST) with the minima in the local morning at around 08.00LST. Therefore, in order to produce a self-consistent long-term dataset with minimal bias we corrected the SSM/I data from a number of DMSP satellites, such that the estimates have zero bias with respect to the benchmark estimates produced by TRMM COMB. The step-by-step procedure is as follows

- 1) Benchmark SSM/I F11 to TMI. Calculate and remove the bias in $SGPROF_{F11}$ rainfall estimates associated with differences between the TMI and SSM/I F11 sensor. The mean error of co-temporal and co-located $SGPROF_{F11}$ and $TGPROF$ instantaneous estimates was derived over the study region and subtracted from the mean rainfall estimates from $SGPROF_{F11}$.
- 2) Inter-SSM/I bias. Calculate and remove the biases introduced by the use of different SSM/I sensors on board the five DMSP platforms. This involved calculating the mean differences between each $SGPROF_{Fn}$ and benchmarked $SGPROF_{F11}$ estimates for co-temporal and co-spatial SSM/I $SGPROF$ estimates. All the SSM/I $SGPROF$ estimates were then normalised to the benchmarked $SGPROF_{F11}$.
- 3) Diurnal bias. Remove bias of $SGPROF$ estimates due to inadequate sampling of diurnal cycle. This was achieved by calculating the ratio of the average rainfall for each grid cell for the (sensor and platform adjusted) $SGPROF$ estimate at the SSM/I overpass time to the un-biased average daily mean rainfall calculate from $TGPROF$.

The final step was to benchmark the sensor and platform and diurnally adjusted SGPROF estimates to TRMM COMB using co-temporal and collocated estimates of rainfall between TRMM COMB and the adjusted SGPROF: the bias corrected product is referred to as SGPROF_{BC}.

2.3. Comparison and combination of areal rainfall from gauged data and remote sensing

For the purposes of hydrological modeling it is necessary that the input rainfall data from both gauges and satellite have consistent statistical characteristics. It is known that TRMM rainfall products have errors (e.g. Adeyewa and Nakamura, 2003) such that a correction to endure consistency with gauges is to be expected. That the SGPROF_{BC} product is benchmarked to a single algorithm (TRMM COMB) makes this process simple in principle. Ideally, the correction would be derived by comparing coincident SGPROF_{BC} and IDW interpolated gauge data over the Okavango River basin. However, this is problematic due to the different time periods covered by the datasets over the basin. Therefore, two gauge/satellite comparison exercises were conducted. First, monthly satellite estimates were compared to the eight global telecommunication system (GTS) gauges operating within the wider Okavango region (interpolated to a 0.5 degree grid) over the period 1991-96. Second, the frequency of exceedence of SGPROF_{BC} satellite rainfall estimates for the period 1991 to 2002 were compared with the spatially average estimates based on gauge data for the 1960 to 1972 period. An independent assessment was also made of on five gauges from the nearby region of northwest Zambia (12-15°S, 20-25°E) for which the rainfall records are continuous from 1960-2001.

Spatial patterns of the distribution of rainfall based on gauged data and on satellite derived data SGPROF_{BC} were compared as a form of validation of the consistency of the series. With regard to absolute amounts, in order to extend the use of the Pitman rainfall-runoff model

from the 1960-1972 period used for model calibration to the 1991-1997 period used for validation of the model, it was necessary to ensure that the satellite rainfall data had consistent statistical characteristics as the gauged rainfall data. A correction equation was developed by comparing the gauged and satellite rainfall frequency curves for three of the sub-basins (Cuchi, Mucundi and Cuito, Figure 1) and manually fitting a simple power function.

3. Results

3.1. Evaluation of gauge interpolation method

For the co-kriging gauge interpolation a number of physiographic variables showed a significant correlation with mean annual rainfall, in terms of spatial structure (WERRD Annual Report, 2004). It appeared that rainfall is positively associated with altitude, proximity to water divide, slope steepness and vegetation density. The highest correlation existed between the rainfall and the African Seasonal Land Coverage (SLC) vegetation classification, and this was subsequently used in the co-kriging interpolation (ibid). Cross-validation revealed that the standard predicted error (SE) for wet season months was lowest for the Nicholson dataset interpolated by IDW and highest for the extended dataset interpolated by co-kriging. However, differences in SE between the methods are relatively small and not statistically significant. Therefore, the accuracy of the interpolated gauge data is largely insensitive to the choice of interpolation method used and to the gauge dataset.

Figure 3 shows the mean annual rainfall as estimated using the various datasets and gauge interpolation methods for 1960-72 and the remote-sensing derived rainfall for 1991-2002. For the period 1960-1972, the extended datasets show a higher rainfall area over Cuito that does not appear with the Nicholson dataset. Little difference can be noted between the different interpolation methods (IDW and co-kriging). This higher rainfall area is also apparent in the remote-sensing derived rainfall, though located slightly further south.

This difference can be further illustrated by comparison of the statistical characteristics of mean wet season rainfall for the three spatially interpolated rainfall datasets. For the easterly situated Cuito sub-basin, both datasets based on the extended rainfall database provided significantly higher rainfall averages than given by the Nicholson database (Figure 4). In contrast, for the Kubango headwater sub-basin, situated in the western parts of the Okavango basin, there are no statistically significant differences in mean the wet season rainfall (Figure 4) between the datasets.

Simulated streamflow generation with the Pitman rainfall-runoff model for 1960-1972 was shown to be without consistent differences between the three datasets at Kubango. At Cuito, the annual flow volume was significantly higher when using the extended databases than with the Nicholson database, both when using IDW (31 mm) and co-kriging (26 mm). The coefficient of efficiency of the hydrological simulations (Nash and Sutcliffe, 1970) was 0.63 using the extended gauge data with IDW interpolation but only 0.02 using the Nicholson data with IDW and 0.24 using the extended data with co-kriging (Figure 5). Overall, the results indicate the extended gauge dataset interpolated with the IDW method is the most appropriate for the subsequent hydrological modeling due to the improved representation of important features of the spatial structure of rainfall especially in the eastern region where one important rain gauge was added. The application and validation of the Pitman model for simulation of monthly flow in the Okavango River, using the extended database interpolated with the IDW method is described in Hughes et. al (this issue).

3.2 Satellite based rainfall estimates

The mean rainfall according to the corrected SSM/I is shown in Figure 3(d). It is clear that the satellite estimates replicate well the north-south gradient in rainfall across the Okavango basin. The temporal variation of the mean rainfall estimates using SGPROF and SGPROF_{BC}

over the wider Okavango region shows that the satellite methods estimate the annual cycle of rainfall well, and that SGPROF_{BC} suggests peak wet season rainfall to be about 10% higher than the SGPROF estimate. The annual average rainfall for the wider Okavango basin is 0.097 mm hr⁻¹ from SGPROF_{BC} and 0.085 mm hr⁻¹ from SGPROF. There is evidence of considerable interannual variability with particularly wet (dry) years in 1991-2 and 1997-8 (1992-3 and 1994-5) which corresponds to the Okavango River discharge record (Hughes et al., this issue). The highest monthly rainfall totals are observed in January 1998 (0.32 mm hr⁻¹) and the lowest in January 1993 of (0.26 mm hr⁻¹). It can also be noticed that on a number of years there is an intriguing break in the wet season either at the beginning of the wet season as in 1992-3 and 1994-5 or at the end of the season as in 1991-2.

3.3. Merging the gauge and satellite rainfall estimates

For the purposes of hydrological modeling it is necessary that the input rainfall data from both gauges and satellite have consistent statistical characteristics. However, direct comparison of the IDW interpolated gauge data products and the satellite estimates is problematic due to the different time periods covered by the datasets. Two gauge/satellite comparison exercises were conducted. First, monthly satellite estimates were compared to the eight global telecommunication system (GTS) gauges operating within the Okavango region (interpolated to a 0.5 degree grid) over the period 1991-96. The results indicate that the satellite estimates have a mean bias of 20%. Unfortunately only two of these gauges are located in the Angolan highlands so these data can only be taken to provide limited representation of rainfall variability in this part of the catchment. Second, SGPROF_{BC} satellite estimates and independent gauges were compared over a nearby region of northwest Zambia (12-15°S, 20-25°E) for which the raingauge record is continuous from 1962-96 and consists of five gauges. This Zambian region has similar rainfall related processes and conditions to

the Angolan highlands, such as altitude and large scale circulation features. Therefore, a valid comparison can be made for the correction of the satellite data. The time series of monthly gauge rainfall amounts from northwest Zambia and the Angolan highlands for 1960-1972 clearly show a close similarity of rainfall records between the regions (Figure 6). Comparison of the SGPROF_{BC} and gauge based rainfall estimates for the Zambian region (1991-1996), for only grid cells with gauges in, indicates that the satellite estimate is substantially higher, especially during wet years (Figure 7), providing further evidence of an approximate 20% overestimation by SGPROF_{BC} relative to the interpolated gauge data. From the comparison of Zambian gauge and SGPROF_{BC} estimates it was found that the magnitude of error in SGPROF_{BC} monthly rainfall was proportional to rainfall such that the correction should be non-linear. The correction was derived by fitting a simple power function to the satellite-gauge data (Eq. 2).

$$P_{org} \leq 150 : P_{cor} = P_{org} \quad (\text{Eq. 2a})$$

$$P_{org} > 150 : P_{cor} = 8.8 * P_{org}^{0.56} \quad (\text{Eq. 2b})$$

Where: P_{org} is the uncorrected monthly satellite derived rainfall (mm), and P_{cor} is the corrected satellite derived rainfall (mm). The regionally corrected SGPROF_{BC} estimates are also shown in Figure 7 and show close agreement with the gauge data. On average for the Okavango basin, the revised satellite SGPROF_{BC} data for the period 1991-1996 was 19% lower than the original, thereby effectively removing the estimated bias in the satellite estimates.

A final test of the applicability of the revised SGPROF_{BC} data was the output from the rainfall-runoff model, when driven by the combined time series of spatially interpolated gauged rainfall data and corrected satellite derived data. Both the water balance and the river discharge (Hughes et al., this issue) was satisfactory modelled with the merged rainfall time

series, based on gauged data from 1960-1972 and corrected satellite data from the 1990s (Figure 8).

3.4 Basin water balance

The basin mean discharge/rainfall ratio over the entire study period is close to 6% (Figure 8). This figure can be compared with estimates for other river basins in Africa by Oki et al. (1995) based on a synthesis of atmospheric and surface water budget calculations. This discharge efficiency for the Okavango basin lies within the expected range associated with the gradient from the humid tropics (e.g. Congo River, 23%) through the semi humid zone (e.g. Zambezi River, 10%) to the semi arid zones of southern Africa (Orange River, 1.2%). Annual discharge efficiency values for the Okavango River range from 4.5% to 10.5% and show a negative association with annual rainfall (Figure 8). Based on spatially interpolated gauged rainfall data and gauged river discharge data from 1965-1970, an assessment of spatial variability of monthly water balance was made for selected sub-basins (Figure 9). The prevailing geological and hydro-climatological factors interact to produce a geographically very heterogeneous pattern of the water balance. Overall, however, along a North-South transect of decreasing rainfall a decrease in the river discharge/rainfall ratio is evident. The dynamical range of the hydrograph in the East is reduced considerably compared to the western sub-basins (Figure 9).

4. Discussion

Contrary to the many studies indicating that interpolation methods taking into account the spatial correlation of rainfall e.g. kriging outperform more simplistic methods (e.g., Lebel et al., 1987; Weber and Englund, 1994) this study found slightly higher SE on cross-validations of co-kriging as compared to IDW. This is probably due to

the spatial and temporal inconsistencies in the co-kriging variogram structure. However, with the exception of a few sub-basins, the results from using IDW and co-kriging were quite similar, indicating that with the existing scarce network of rainfall stations and limited access to metadata about the stations, the choice of interpolation method is less important than the inclusion of key rainfall stations. Results from the cross-validations do not reveal anything of the quality of extrapolation to regions where no rainfall stations are included in the analysis, such as the north-eastern parts of the basin (Figure 2). The extended gauge dataset includes one station, Longa (marked with a triangle in Figure 2) which contributes higher rainfall totals in the north-eastern parts of the basin, compared to that given by the Nicolson database (Figure 3). This higher rainfall is consistent with the spatial distribution of satellite produced rainfall estimates. Streamflow volume simulations were found to be higher with the extended datasets and showed better correlation with the observed flow at Cuito sub-catchment (Figure 5). This indicates that rainfall in the north-eastern sub-catchments was better represented when the extra rainfall gauge at Longa was included (in the extended datasets), despite the contradictory results from the cross-validation. Again, interpolation method was less important than inclusion of key rainfall stations.

Correction of satellite derived rainfall data based on direct comparison with rain-gauges within the basin is especially problematic in this case due to the absence of gauge data during the satellite epoch, since the basin gauge and satellite data are not coincident in time. Comparison of coincident satellite and gauge data in adjacent regions outside the basin indicate that the satellite estimates have a bias of approximately +20%. A non-linear correction based on this was applied and found to be satisfactory from the model runs. Another potential correction method would be to use the hydrological model driven by various satellite rainfall estimates, in order to find the satellite rainfall correction factors that gave an optimal fit between monitored and modelled flow. However, the selected rainfall corrections would then be dependent on the selected set of calibrated parameters of the hydrological model. In addition, the selected approach allowed a validation of the calibrated

1960-1972 wetter period on the dry 1990-period. Although the satellite correction algorithm seems to be adequate, an operational use of satellite data should preferably involve a more comprehensive satellite rainfall estimate calibration procedure. An intensive campaign of monitoring with a representative spatial detail for a limited time-period (a few years), would improve this procedure.

5. Conclusions

Hydrological modeling of large river basins is dependent on the availability of high quality datasets. Numerous river basins in the world are characterised by limited measurements of key hydrological parameters such as precipitation. This is the case in data sparse regions such as southwest Africa. This lack of data often presents problems for accurate modeling and, in turn, sustainable management of the water resources of these basins. In this paper, we have described the development of a combined gauge and satellite long term rainfall dataset with the necessary spatial and temporal resolution for hydrological modeling applications for the Okavango River basin. The paper has shown that for this data sparse region a combination of spatial modeling of rain gauge readings and the satellite data based rainfall retrievals can provide a consistent rainfall database that forms the basis of further hydrological investigations. These data enable the quantification of the water balance for the Okavango river basin and sub-basins. The work tested methods of gauge interpolation and indicated that the method is less important than the availability of rainfall stations, and more effort should therefore be put on finding all possible sources of rainfall data, especially to fill in important spatial gaps. In quantifying interpolation accuracy, cross-validation alone was found not to be an appropriate test of accuracy datasets when gauges are not representative of large parts of the basin due to their geographical location. In this case, the hydrological model itself can be a useful tool to establish which gauge data set is most appropriate. Merging the discontinuous

and non-coincident gauge and satellite datasets into a unified dataset is problematic and we have sought to remove systematic biases from satellite rainfall estimates. The merged dataset was also tested by using the hydrological model. The paper highlights the need for improved long term data collection in the study region for hydrological modeling in support of water management decision making.

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FIGURE CAPTIONS

1. The Okavango River Basin showing selected sub-basins.
2. Location of rain gauges included in the study, indicating gauge stations from the Nicholson database (circles), gauge stations from other sources (squares) and Longa station (triangle). Graduated colour indicates the completeness of record for 1960-1972.
3. Mean annual rainfall over the basin as determined by (a) Nicholson database interpolated with IDW (b) extended rainfall database with IDW interpolation (c) extended rainfall database with co-kriging interpolation (d) satellite estimates from SGPROF_{BC} (1991-1997). All values are expressed in standard deviations from the area averaged mean.
4. Boxplots showing the median, quartiles and range of the wet season rainfall (Nov-April) from 1960-1972 for (a) the Kubango (west) and (b) Cuito sub-basins (east) (cf. Figure 1)
5. River discharge (Mm^3), observed and simulated with the Pitman model with various rainfall datasets at (a) Kubango and (b) Cuito (cf. Figure 1).
6. Monthly interpolated gauge based rainfall for the Angolan highlands (12-15°S and 15-20°E) and for northwest Zambia (12-15°S and 20-25°E) from 1960-1972.
7. Monthly estimates of rainfall for north west Zambia (12-15°S and 20-25°E) from 1991-1996 as estimated by gauges ('historical'), satellite SGPROF_{BC} ('satellite'), and regionally corrected SGPROF_{BC} ('revised')
8. Observed rainfall, observed and simulated water balance (Q/P) and observed and simulated river discharge (cf. Hughes et al., this issue), estimated with the merged rainfall time series (a combination of gauged data from 1960-1972 and corrected satellite data from 1993-1997).

9. Observed precipitation (P), discharge (Q) and water balance (Q/P) for selected sub-basins (1965-70).

Figure 1

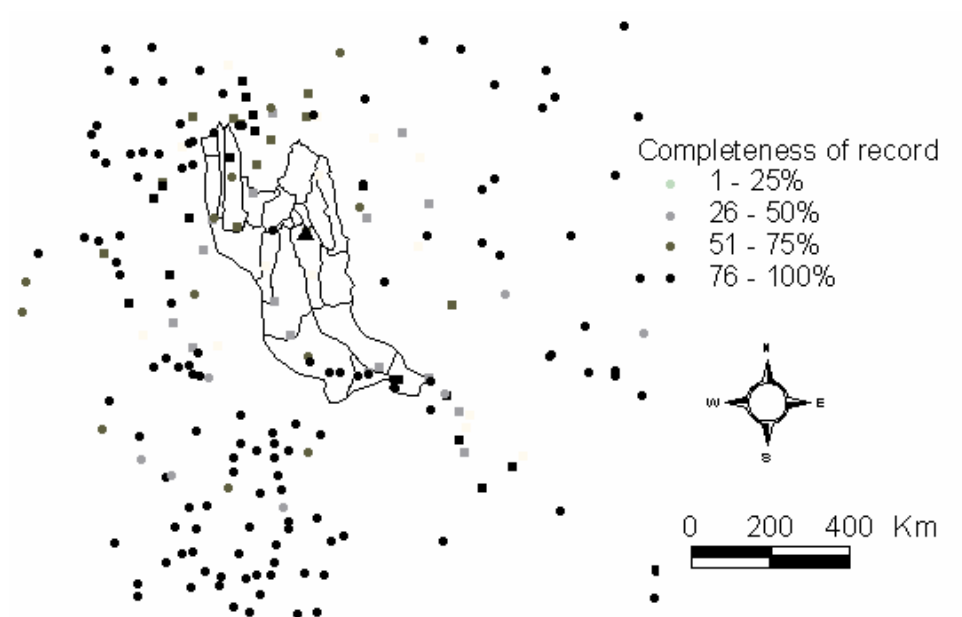


Figure 2

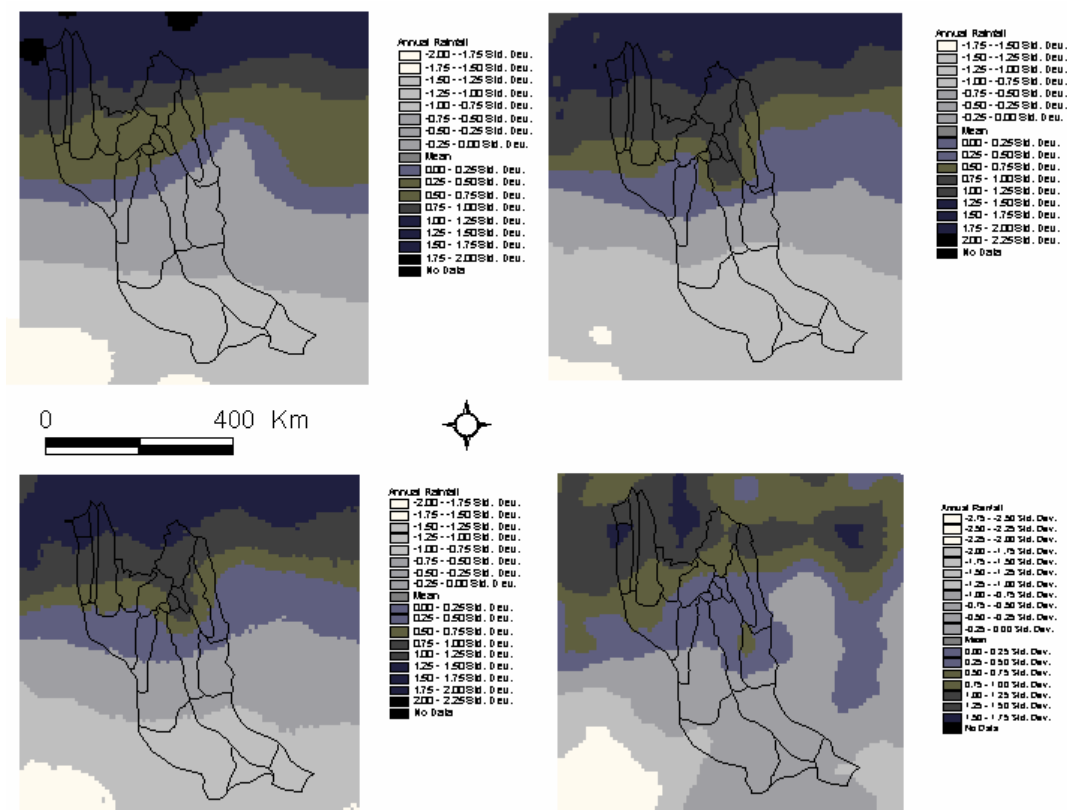


Figure 3

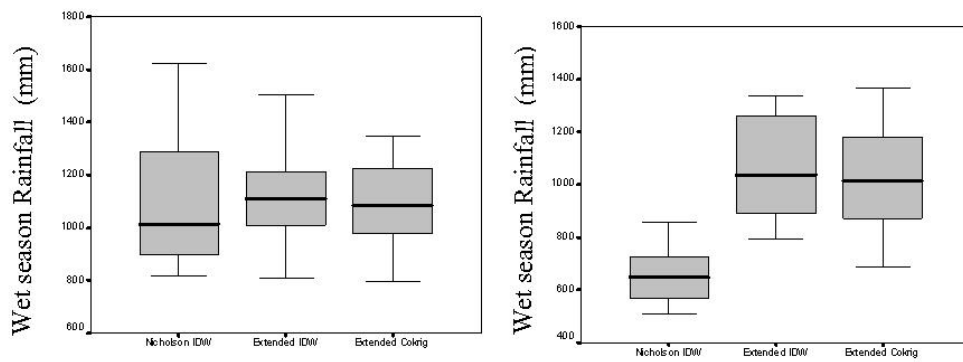


Figure 4

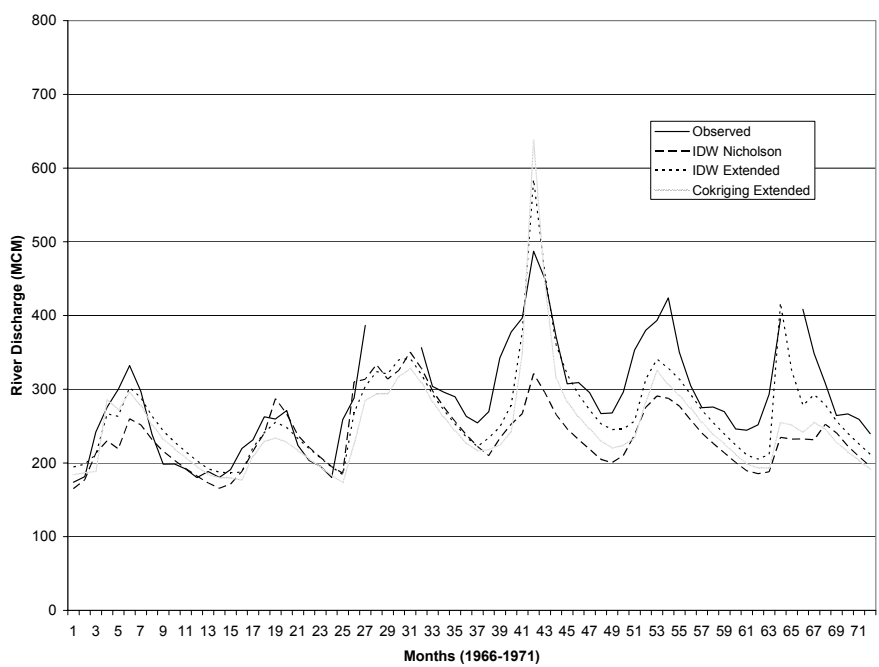
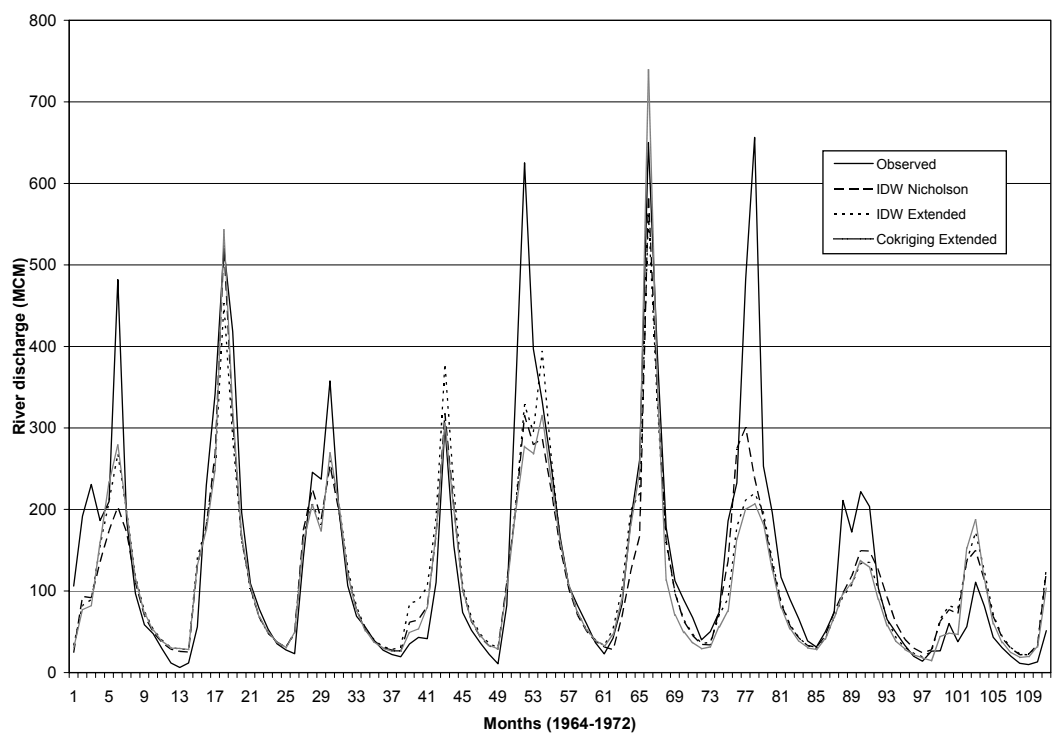


Figure 5

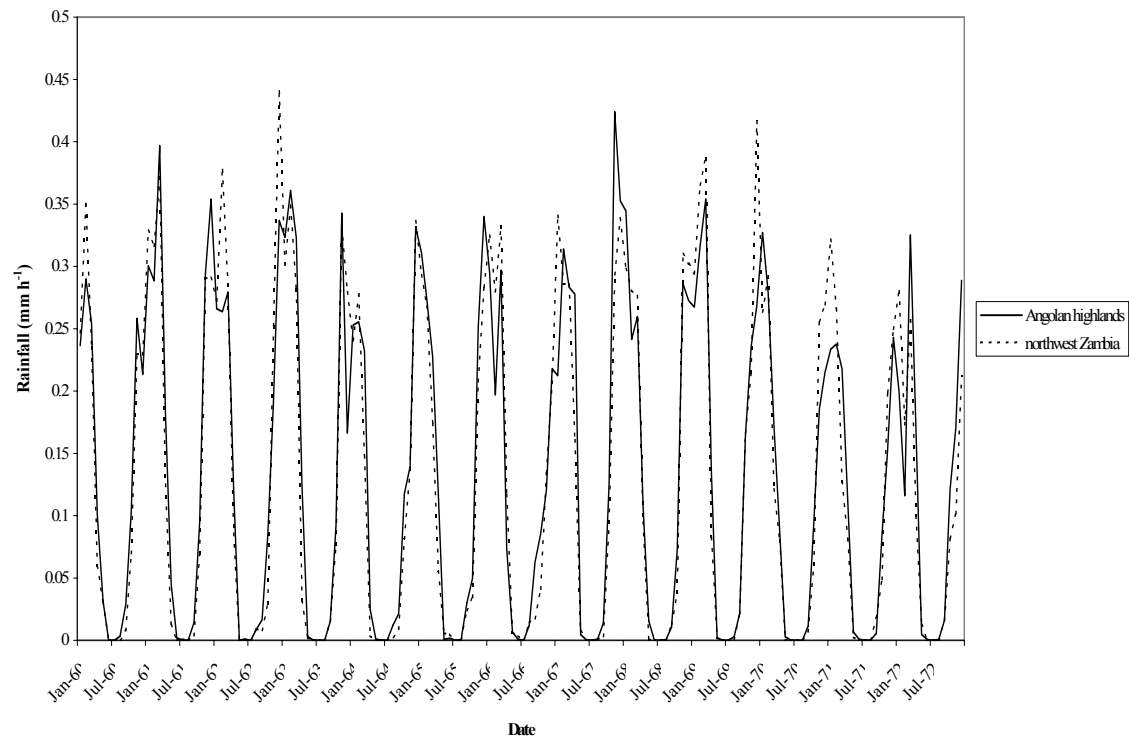


Figure 6

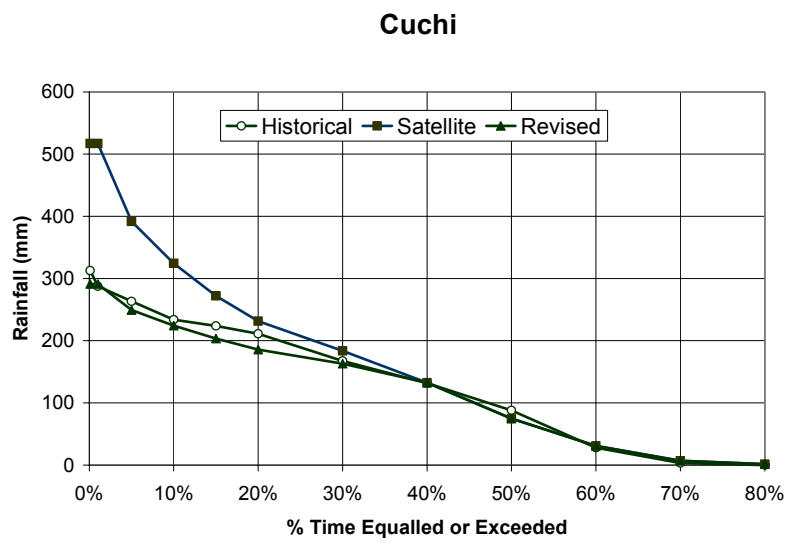


Figure 7

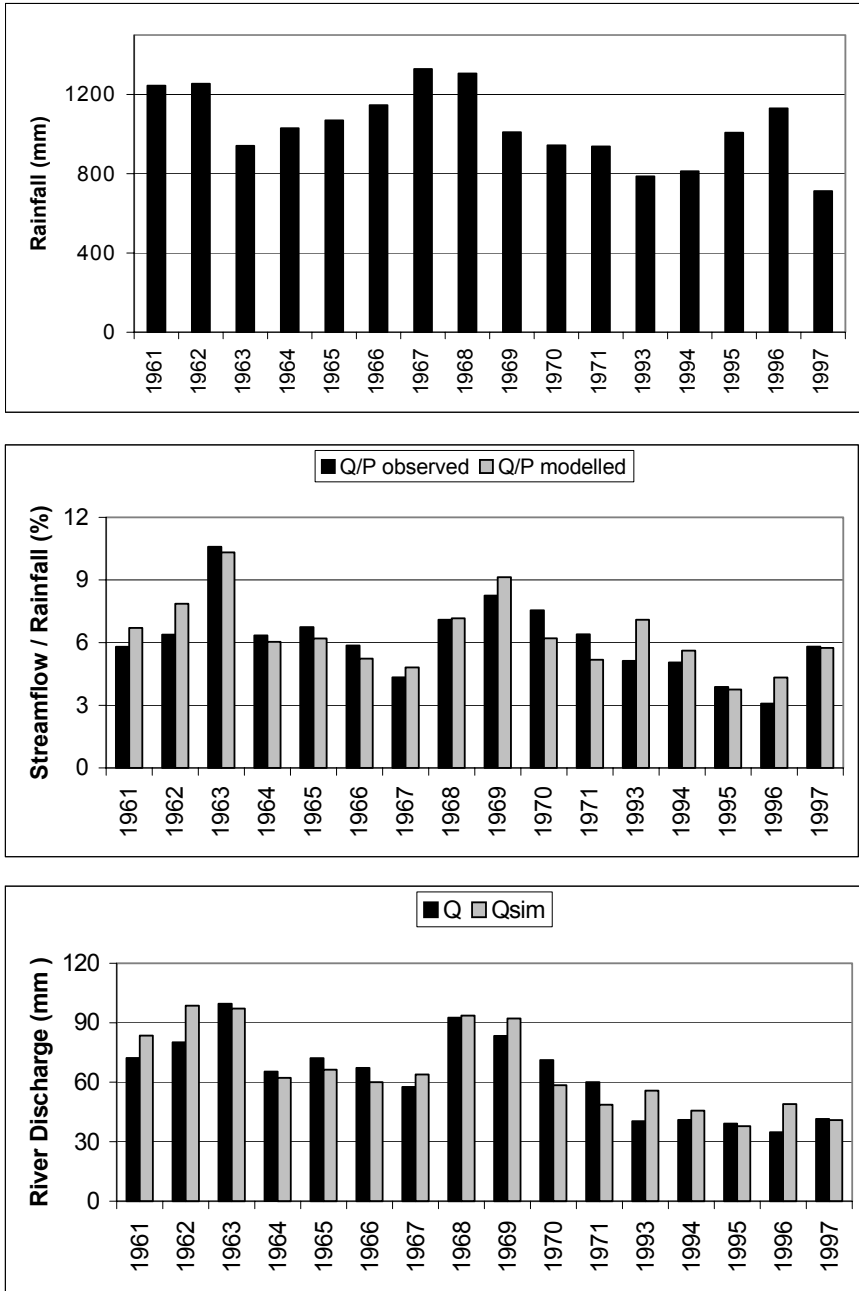


Figure 8

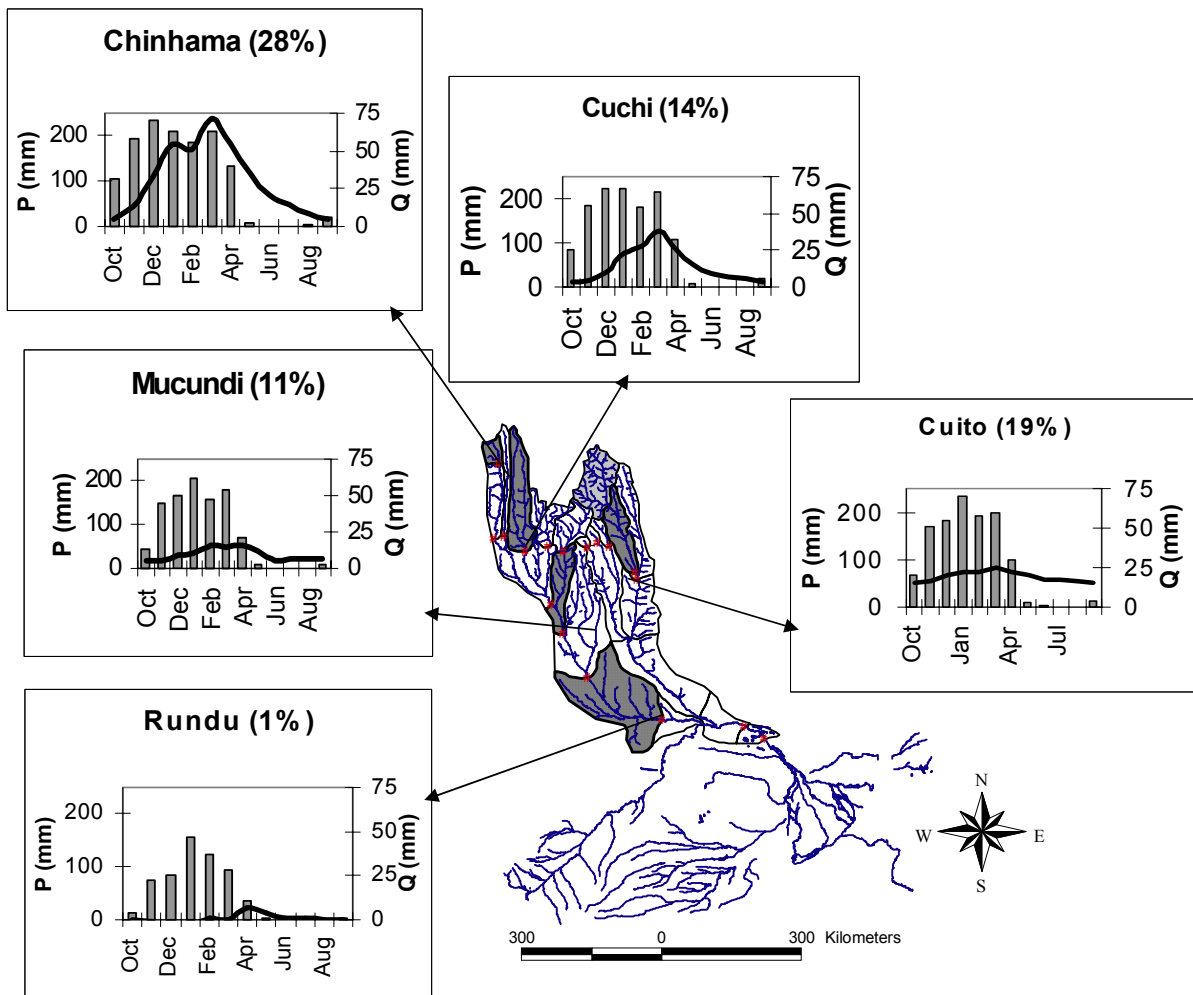


Figure 9